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Smartphone based detection and classification of poultry diseases from chicken fecal images using deep learning techniques

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ABSTRACT

Human demand for animal products is increasing, forcing the agricultural industry, particularly poultry farming, to increase the quantity of its output. Increased poultry farming can lead to increased transmission of infectious diseases, resulting in widespread poultry death and significant economic losses. Traditional techniques for detecting diseases in poultry involve manual methods that are labor-intensive, time-consuming, and error-prone. Furthermore, the interpretation of the results often requires the expertise of trained professionals. These limitations can impede timely disease detection and increase the risk of the disease spreading throughout the flock, which can have severe consequences. This paper presents a detection and classification system for poultry diseases. The system was developed using two core algorithms: YOLO-V3 object detection algorithm and ResNet50 image classification model. YOLO-V3 was used to segment region of interest (ROI) from faecal images while ResNet50 was used for classification of the segmented image into four health conditions: Health, Coccidiosis, Salmonella, and New Castle Disease. The models were trained on 10,500 chicken faecal images collected from Zenodo open database. Oversampling and image augmentation techniques were applied to the dataset to handle class imbalance prior to training the ResNet50 model. The YOLO-V3 object detection model, implemented in Darknet, achieved a mean average precision of 87.48% for detecting regions of interest (ROI), while the ResNet50 image model demonstrated a classification accuracy of 98.7%. Based on our experimental findings, the proposed chicken disease detection and classification system exhibits the ability to accurately identify three prevalent poultry diseases. Therefore, this system can prove to be a valuable tool for assisting poultry farmers and veterinarians in farm settings.

1. Introduction

Animal agriculture is extremely important to the world's rising population. Animal products provide nutrient-dense meals that help people of all ages stay healthy in communities all over the world. The agriculture business must continue to improve its efficiency and quantity of production as human demand for animal proteins increases [1]. Poultry is widely recognized as a valuable source of protein, and many countries will be forced to increase output, resulting in an increase in the number of farms housing birds at high densities. Furthermore, Poultry farming is crucial for socioeconomic development of developing countries because it provides eggs and meat, which help to ensure food and nutrition security at the household, regional, and national levels. moreover, it provides cash income to the population and adds more than a hundred million dollars to the gross domestic product of a country [2, 3]. As poultry farming Increases, it can promote increased transmission of infectious illnesses among birds which can cause widespread death in poultry and significant economic losses [4]. Every year, 69 billion chickens are reared for meat production around the world [5]. However, not all of them end up on people's tables. Several million chickens do not make it through the rearing process and are likely to be rejected at the butcher due to sickness, scrapes, bruises, and other symptoms of mistreatment. Given the disparity between food accessibility and hunger for certain individuals, especially for farmers, slaughterhouse rejection of hens can be a significant source of financial loss [6–8]. The high frequency of chicken diseases can be linked to a lack of biosecurity, low vaccination coverage, unscientific poultry management methods, and essentially non-existent poultry veterinary interventions throughout the

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country, particularly in the vast poultry production sector. The most common chicken diseases include fowl cholera, helminth infestation, salmonella infections, avian coccidiosis, and Newcastle disease [9,10].

Salmonella is a gastrointestinal infection. Infected birds can recover after a period of time, but some continue to discharge bacteria in their droppings for months [11]. When placed on permanent bedding, it is quite impossible to rid a salmonella-infected flock of the virus [11]. Its symptoms include weakness, loss of appetite, stunted growth, and white, loose faeces. If young chickens show indicators of significant mortality (up to 100%) and irregular growth [11]. Biochemical testing of chicken faces employing lysine iron and triple sugar iron agar slants can detect the presence of salmonella in addition to the symptoms [12]. On the other hand, Coccidiosis is caused by phylum Apicomplexa, family Eimeriid protozoa. The majority of Eimeria species infect different parts of the intestine in chickens [13]. The infection is quick (4–7days) and is marked by parasite proliferation in host cells as well as significant destruction to the intestinal mucosa [14]. Coccidia in poultry are usually host-specific, with different species parasitizing different regions of the gut [14]. Its symptoms include slowed growth, a high percentage of visibly unwell birds, severe diarrhoea, and a high fatality rate. The amount of food and water consumed is low. Weight loss, culling, decreased egg production, and higher mortality may occur as a result of outbreak [14]. The presence of this disease can be also determined by the location in the host, the appearance of lesions, and the size of oocysts. Oocysts in faeces or intestinal scrapings are a simple way to confirm Coccidiosis infections [14]. The other most common poultry disease, new castle disease, is a highly contagious bird disease that affects both domestic and wild birds [15]. It affects birds and poultry's respiratory, neurological, and digestive systems. Because the disease is so deadly, many birds and poultry die without showing any symptoms. A state of prostration and depression in the birds, with ruffled feathers; greenish white diarrhoea; and, in survivors, the head turned to one side, a condition known as torticollis, as well as paralysis of the legs, wings, or other neurological signs, are all common clinical signs of new castle disease [15].

The research of computer vision, imaging processing and pattern recognition has made substantial progress during the past several decades. Nowadays, due to availability of large amount of data and sophisticating algorithms such as deep learning, researchers and industries are employing the technique to solve variety of problems ranging from simple object detection up to complex scene understanding [16]. Especially in health care applications, computer vision and deep learning become successfully for disease detection, classification, and localization.

Predicting infectious disease in poultry is becoming possible as new technologies are increasing the availability of data that can be utilized in predictive models [4]. With the development of computer vision systems, computerized disease diagnosis and detection of sick birds have been reported in several studies [17]. performed a skeleton analysis for early detection of sick broilers by image processing. Additionally, Zhuang and Zhang [18] reported on a sick broiler detector based on deep learning techniques. The analysis of chicken droppings by image processing and deep learning for sick bird detection is reported by Wang et al. [19]. However the study it limited to detecting the abnormality of the faecal image and does not detect the presence of a disease directly. Similarly, a deep Convolutional Neural Network (CNN) model was developed to diagnose poultry diseases by classifying healthy and unhealthy fecal images by Machuve et al. [20]. However, the models were trained using entire acquired images without utilizing object extraction (detection). This approach may result in reduced classification accuracy, as the presence of non-target objects in the images may negatively impact the training process.

The objective of this study is to develop an automated computer vision system capable of identifying and classifying chicken diseases through the analysis of chicken facial images. To achieve this goal, we employed advanced object detection algorithms using YOLO v3 and pre-trained image classification algorithms using ResNet-50 to detect and classify prevalent poultry diseases. Additionally, a mobile application interface was developed to ensure easy access to the system for poultry farmers and veterinarians.

2. Methods

This research presents a mobile-based automated chicken disease detection and classification system. The system uses the image of the chicken droppings to predict the existence of the three most commonly occurring poultry diseases: Salmonella, Coccidiosis, and New Castle Disease. The development of the system includes gathering and pre-processing image datasets, creating augmented images, segmenting region of interest, training & testing image classification deep learning model, and developing a mobile app interface for the system. Fig. 1 shows the summary of the steps involved in the study.

2.1. Dataset

A total of 8067 annotated poultry fecal images were collected from Zenodo open database [21]. The dataset was taken in Arusha and Kilimanjaro regions in Tanzania between September 2020 and February 2021 using Open Data Kit (ODK) app on mobile phones. The dataset contains four classifications: Healthy, Salmonella, Coccidiosis, and New Castle disease. Fig. 2 shows sample images of the dataset.

2.2. Dataset pre-processing

The dataset is made up of four image classes with varying sizes of 2625 (32.5%) Salmonella, 2476 (30.7%) Coccidiosis, 2404 (30%) Healthy, and 562 (6.96%) New Castle Disease. As a result, the data is skewed, with Salmonella being the most common and New Castle Disease being the least common. The performance of most typical classifier learning methods, which assume a somewhat balanced class distribution and equal misclassification costs, can be significantly reduced when classifying data with an uneven class distribution [22]. To address this issue, the dataset has been oversampled before being fed into the classifier deep neural network model. Oversampling is a data science technique that duplicates samples from a minority class to create an evenly distributed dataset. Common oversampling techniques are ROS (random over sampling) and SMOTE (Synthetic minority oversampling technique) [23]. ROS involves randomly selecting examples from the minority class, with replacement, and adding them to the training dataset. SMOTE, on the other hand, generates synthetic images from the minority class using the k-nearest neighbours' algorithm. While SMOTE appears to be useful in most circumstances with low-dimensional data, it does not reduce the bias towards classification in the majority class for most classifiers when the data is high-dimensional [24]. For high-dimensional data such as images, ROS is an ideal oversampling technique. However, in some cases, it may cause an overfitting problem [25]. In this study, ROS was applied to the dataset to generate an evenly dispersed dataset. Then, images are augmented randomly to reduce overfitting problem. This step produced 10,500 images with all classes having equal number of examples.

2.3. Image pre-processing

Region of interest (ROI) segmentation and data augmentation were applied on the images prior to feeding to the deep learning classifier model.

2.3.1. Data augmentation

Data Augmentation refers to a range of approaches for increasing the size and quality of training datasets so that improved deep learning models is then developed [26]. It's a helpful strategy in computer vision for avoiding overfitting during training. Overfitting occurs when a

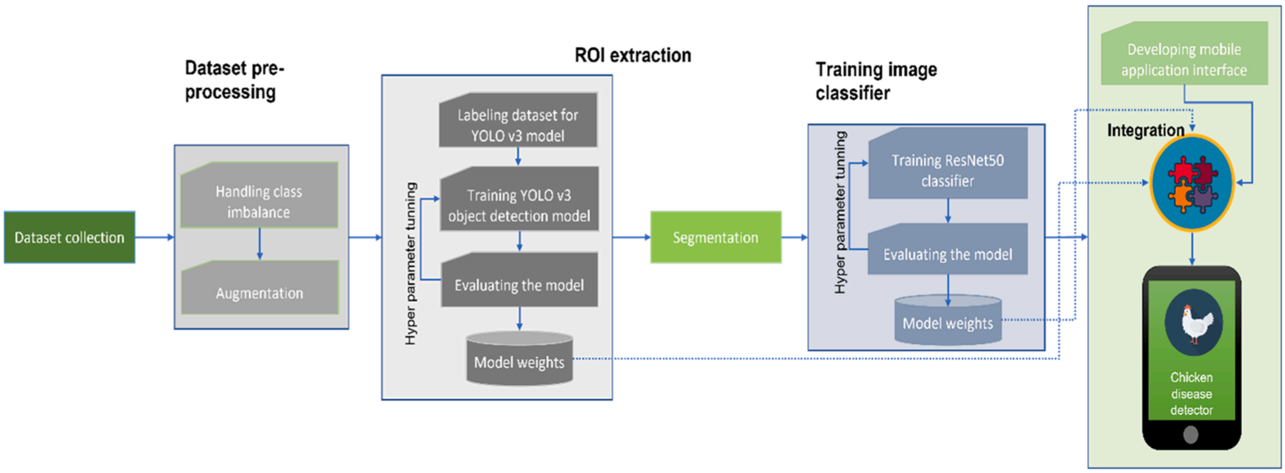

Fig. 1. Summary of the proposed system.

Fig. 2. Sample images of the dataset.

network learns a function with a high variance to perfectly model the training data. In this step, Geometric transformation augmentation techniques such as rotation, zooming, flipping, and shifting were randomly applied to the training images. Fig. 3 provides examples of the augmentation's inputs and outputs.

2.3.2. *Extracting region of interest (ROI)*

ROI extraction is a technique used in image processing to separate the target area from the rest of the image's contents. In this study, YOLO v3 (You only look once, version 3) object detection technique was trained on labelled datasets to detect ROI from faecal images. YOLO v3 is a real-time object detection algorithm that identifies specific objects in videos, live feeds, or images. YOLO uses features learned by a deep convolutional neural network, called darknet-53, and scale features extracted by feature pyramid network (FPN), to detect an object from a given picture scene [27]. The YOLO-V3 algorithm first separates an image into a grid. Each grid cell predicts some number of boundary boxes (sometimes referred to as anchor boxes) around objects that score

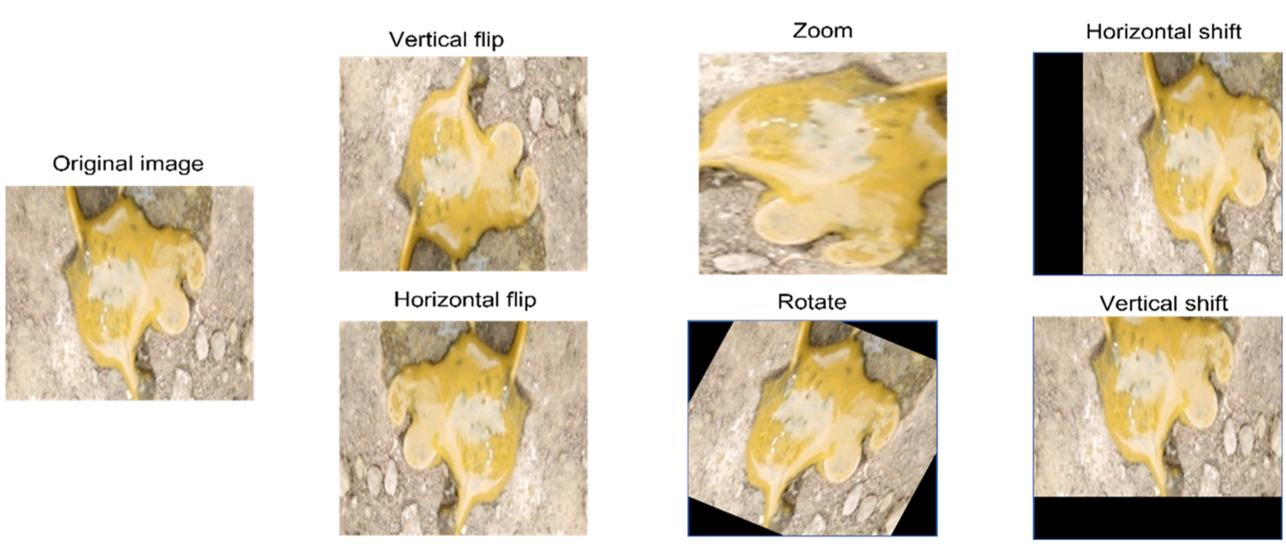

Fig. 3. Image augmentation.

highly with the predefined classes. Each boundary box has a respective confidence score of how accurate it assumes that prediction should be and detects only one object per bounding box. The boundary boxes are generated by clustering the dimensions of the ground truth boxes from the original dataset to find the most common shapes and sizes. Architecture of the YOLO v3 model is illustrated in Fig. 4.

2.4. Training classifier model

Training a deep learning model from start requires a large number of images, as well as high-capacity processor computer. To address this issue, transfer learning approaches allow to leverage an existing model by modifying and retraining and fulfil a new use case. In this study, a pre-trained ResNet-50 was employed for feature extraction. ResNet-50 is a deep CNN model in which the main idea is to use shortcut connections to skip one or more levels [28]. The basic cell blocks in this network are known as "bottlenecks," and they follow the following rules: a layer with the same number of filters has the same number of output feature maps, and if the size of the feature map is lowered, the number of filters is doubled. Down-sampling is accomplished via a two-stride convolutional layer, followed by batch normalization before applying the ReLU activation function [28]. The network architecture of ResNet50 is illustrated in Fig. 5.

The ResNet50 architecture consists of 50 layers, and the process of feature extraction occurs in the early layers of the network. The first layer is a convolutional layer that applies a set of 64 filters of size 7 $\times$ 7 to the input image. Each filter is convolved with the input image to produce a feature map, and this process is repeated for all 64 filters. The resulting set of 64 feature maps is then passed through a max pooling layer, which down samples the feature maps by taking the maximum value of each 2 $\times$ 2 block of pixels in each feature map. This reduces the spatial dimensions of the feature maps by a factor of two and helps to make the features more invariant to small spatial translations in the input image. The pooled feature maps are then passed through four stages of residual blocks, each of which contains several convolutional layers and residual connections. The residual connections allow the model to skip over certain layers and preserve the gradient flow through the network, which helps to alleviate the vanishing gradient problem that can occur in deep neural networks. Each residual block applies a series of filters to the input feature maps to extract more complex and abstract features. The outputs of the residual blocks are then passed through another max pooling layer and a global average pooling layer, which down sample and average the feature maps across the spatial dimensions, respectively. Finally, the resulting set of features is passed through a set of fully connected layers, which use the extracted features to make a prediction about the class of the input image.

After feature extraction, sequence of Dropout and Dense layers were applied to make the final classification. The full architecture of the classifier model used in this study is presented in Fig. 6. The output of feature extraction block is converted into a one-dimensional array using Flatten layer to make it appropriate for fully connected layer. Dropout layer is then applied before final classification layer to reduce the occurrence of overfitting. The final layer has four output units representing four health conditions of chickens: Healthy, Salmonella, Coccidiosis, and New Castle Disease.

2.5. Performance evaluation metrics

Accuracy, precision, recall, F1 score, and ROC-AUC plot were used to evaluate the performance of the models. The metrics were calculated from the model's confusion matrix based on TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) values as demonstrated in Equations (1–4). AUC-ROC plot was used to visualize how well the model can distinguish between classes.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$precision = \frac{TN}{TN + FP} \tag{3}$$

$$F - measure = \frac{2 * Recall * precision}{Recall + precision} \tag{4}$$

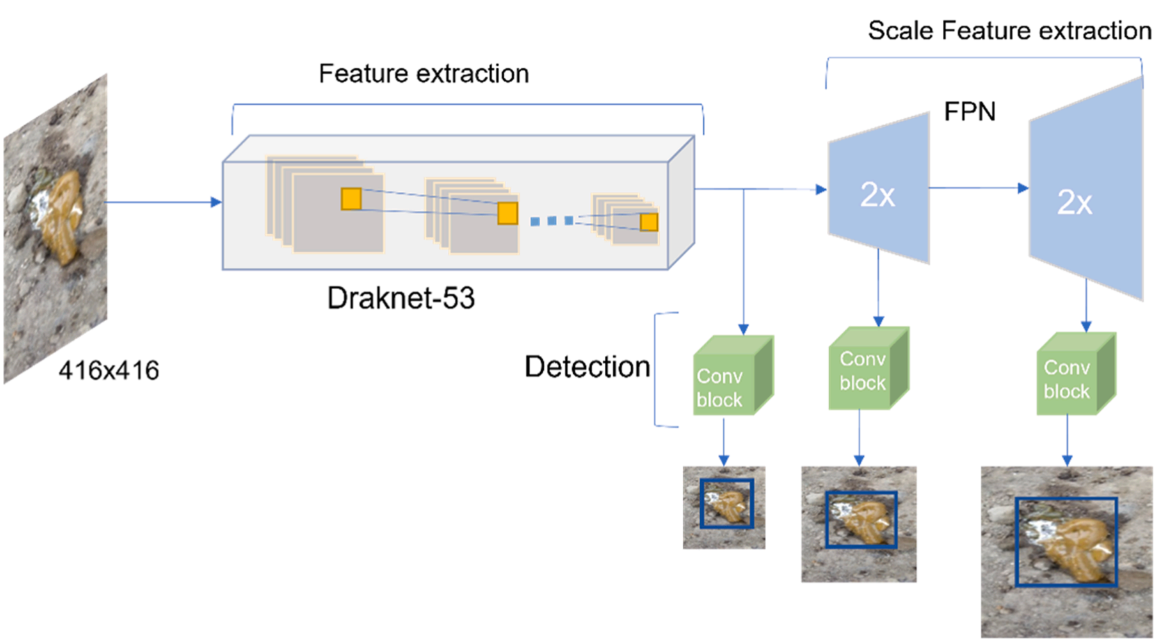

Fig. 4. Architecture of YOLO v3 object detection model.

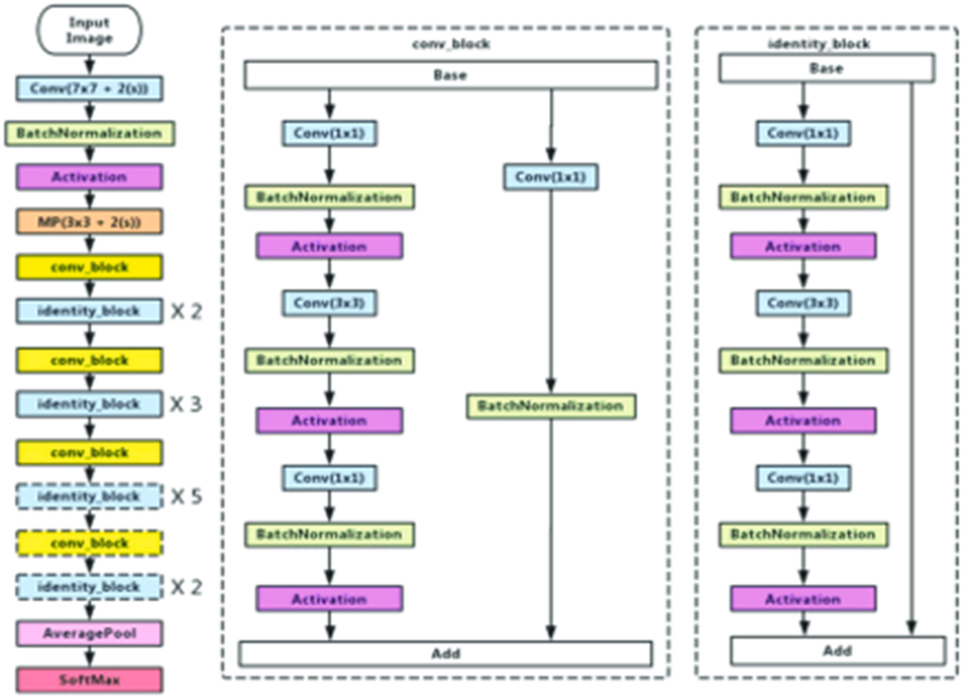

Fig. 5. Network architecture of pre-trained ResNet50 model.

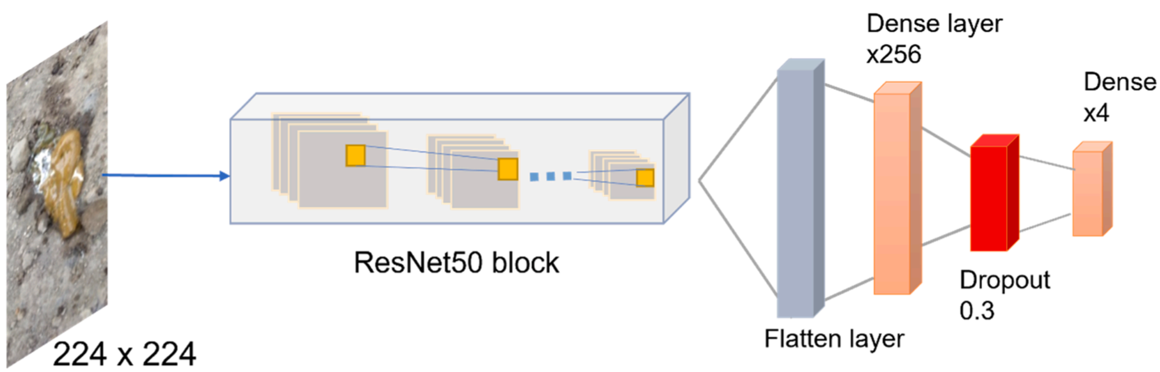

Fig. 6. Full network architecture of chicken disease classifier model used in the study.

3. Results

3.1. Experiment results

3.1.1. Result of ROI extraction

YOLO v3 object detection model was trained on 456 YOLO-labelled images, labelled during the study, using 80/20 train-test split ratio for 2000 epochs and an average loss of 0.16 and 87.48% mean average precision(mAP) were found. The training curve of the model is illustrated in Fig. 7.

The trained model has a capability to locate the target content from the given image and return the box coordinates. The box coordinates will be then used as a reference to segment out the target section from the image. The sample output of YOLO-V3 object detection model is illustrated in Fig. 8.

3.1.2. Results of image classifier

The designed image classifier model was trained on 10,500 labelled images using 80/20 train-test split ratio for 100 epochs. The accuracy of the model was found to be 98.7%. Fig. 9 illustrates the accuracy and loss history of the model during training and validation.

The classifier's ROC curve is presented in Fig. 10. An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters: True positive rate and false positive rate. As shown in Fig. 10, our model has a high true positive rate to distinguish one disease from the other disease.

The figure depicted in Fig. 11 is the confusion matrix of the classifier. It shows the visual representation of the predicted and actual values, with the diagonals showing the true positive count of the model. The false positive and false negative rates are represented in the top-left and right-bottom of the matrix, respectively. The model achieved high accuracies of 98%, 99%, 98%, and 99% for Salmonella, Healthy, Coccidiosis, and New Castle Disease, respectively.

The classifier demonstrated an average score of 98.5% accuracy, with true positive, false positive, and false negative rates of 0.004%, and 0.0043%, respectively. Table 1 displays the precision, recall, and f1-score of the classifier, which were calculated from the confusion matrix.

3.2. Mobile application interface

A mobile based application (named KUKU) was also developed to

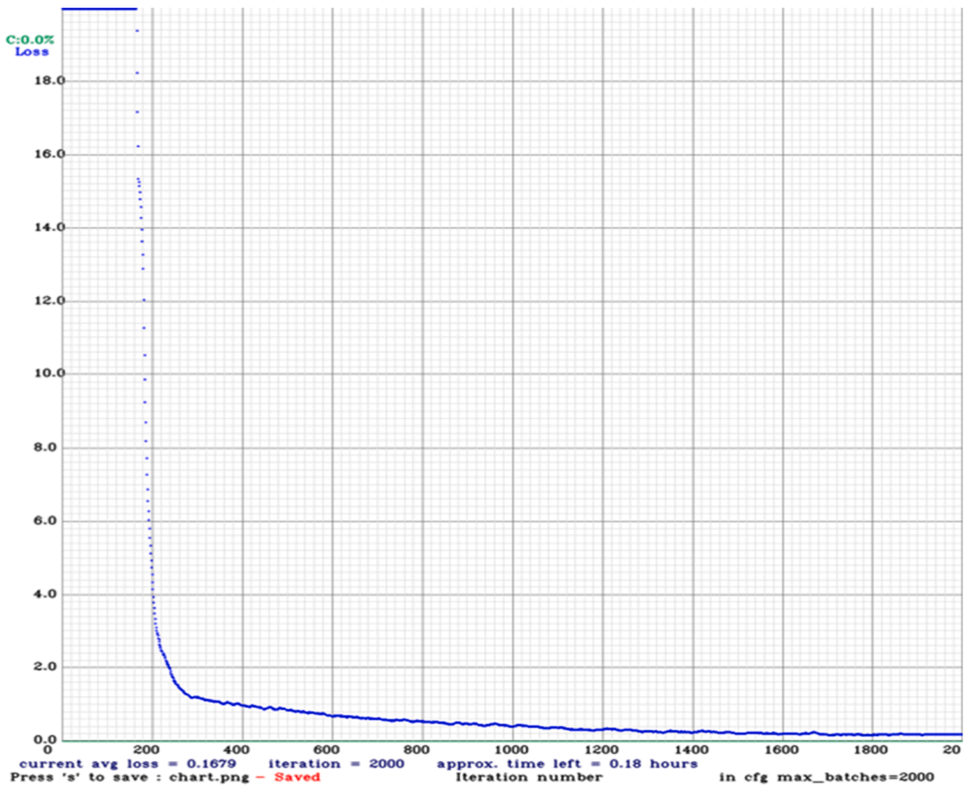

Fig. 7. Training history plot of YOLO-V3 object detection model.

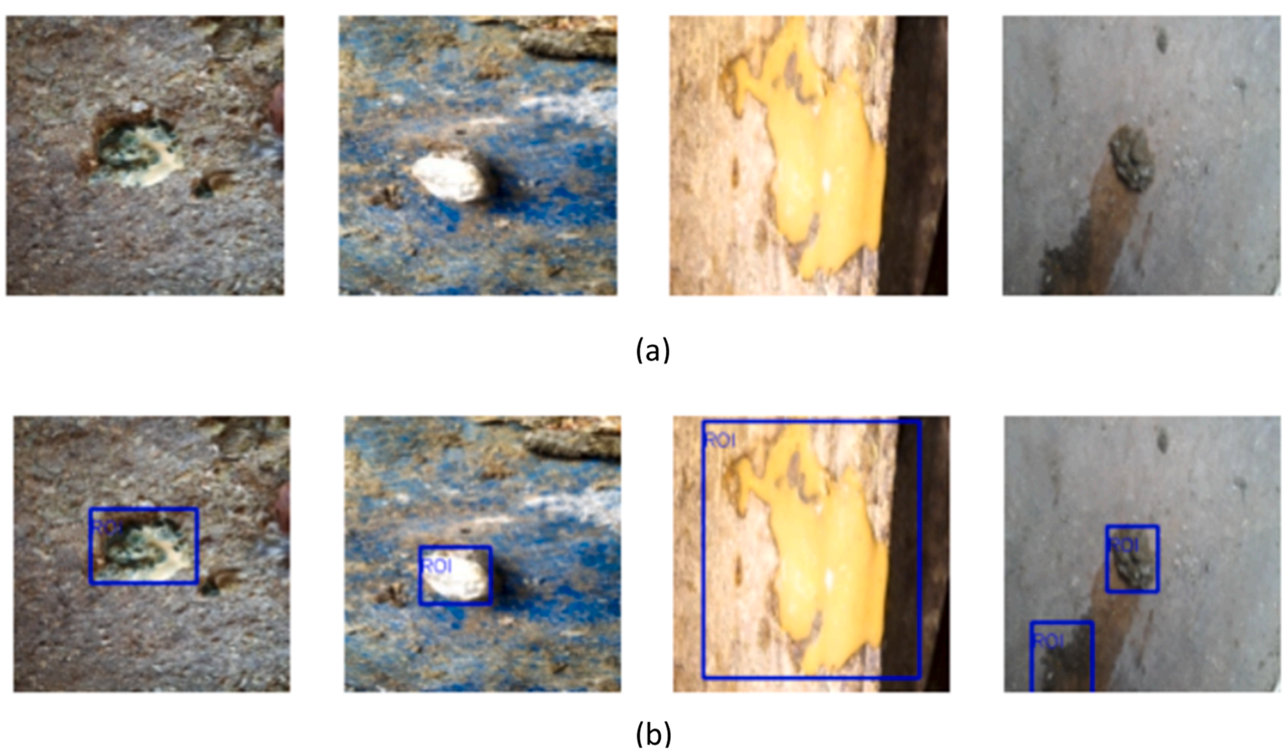

Fig. 8. Sample object detection by YOLO-V3 (a) input image (b) Output image.

make the system easily accessible by end users. The application was developed using flutter mobile application development framework. Sample screens of the app are illustrated in Fig. 12. The application was integrated with the devices camera module for capturing chicken droppings. Once the picture is acquired it will be sent into ROI extraction and disease classifier API, which are implemented using Django, python based back-end application framework.

During model deployment, the trained model was converted to a

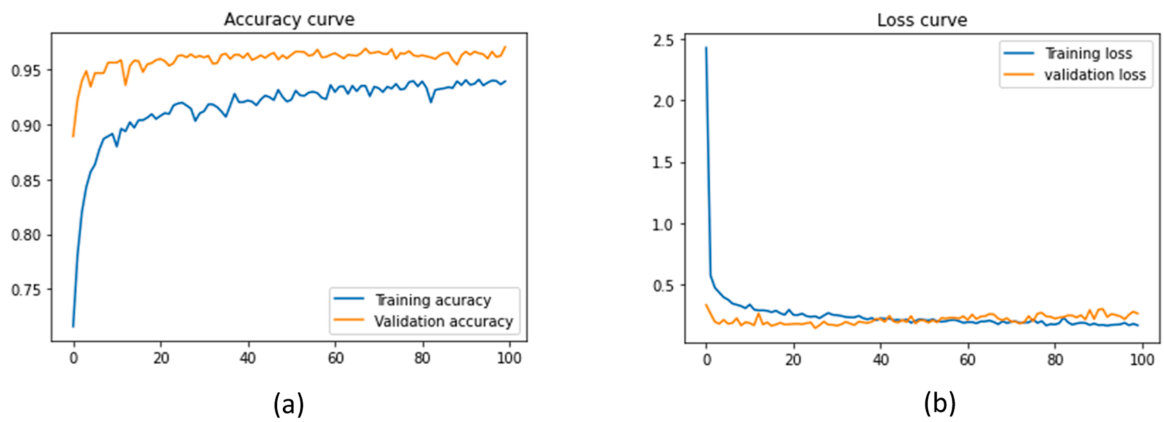

Fig. 9. Training and validation curve of the classifier. (a) Accuracy (b) Loss.

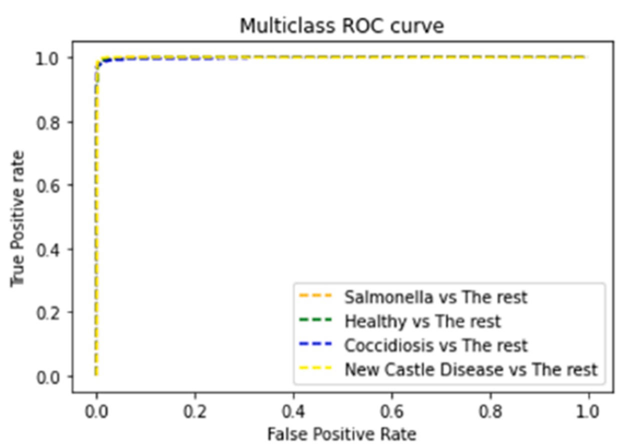

Fig. 10. ROC curve of the classifier model.

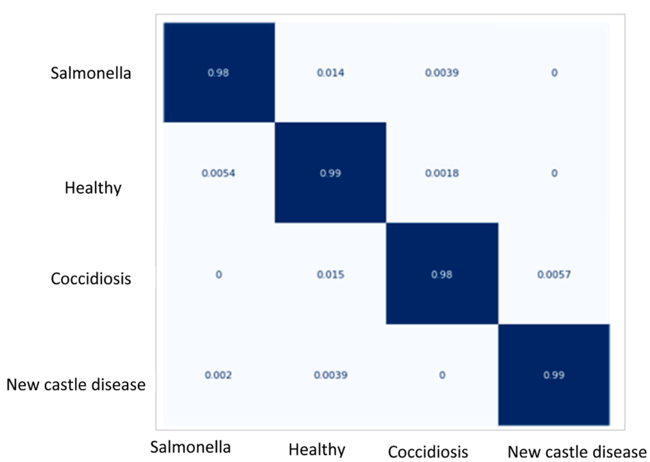

Fig. 11. Confusion matrix of the classifier. Y-axis represents the actual labels of the images while X-axis represents the labels as predicted by the classifier.

Table 1
Results of Chicken disease classification model with different performance metrics.

Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
98.72	98.71	98.71	98.7

format used by deep learning frameworks such as TensorFlow to a format that can be used by mobile frameworks including Core ML (iOS) and TensorFlow Lite (Android). The converted model is then integrated into the mobile app, using a software development kit (SDK) provided by the mobile framework. Then, to improve performance and reduce memory usage, and optimize it for mobile devices, pruning, quantization, and compression were used. Finally, to validate that it works correctly and to ensure that the output matches the expected result in mobile phones, the model was tested on a set of test data.

4. Discussion

Poultry diseases are responsible for several adverse economic and social impacts, especially in developing countries. High frequency of chicken diseases can be linked to a lack of biosecurity, low vaccination coverage, unscientific poultry management methods, and essentially non-existent poultry veterinary interventions throughout the country, particularly in the vast poultry production sector. They lead to high mortality and morbidity of chickens, high medication costs, loss in production and market, and can pose a risk to public health through zoonoses [29]. While implementing diseases prevention methods is an excellent option, early detection of the presence of a disease in the flock plays avital role to carry out an urge treatment and reduce the following impact.

Common poultry disease detection methods include observing the behaviour, physical appearance, type of droppings of the birds, and laboratory examination of sample of chicken's dropping. Some of these methods, however, are prone to human error, while others are difficult to implement on a regular basis.

To address this issue, several poultry disease detection methods based on image processing and deep learning have been proposed. Image processing techniques were used by Zhuang et al. [17]. and Zhang et al. [18]. to analyse the skeleton condition of infected broiler chickens. Wang et al. [19]. used a deep learning technique to classify the state of chicken droppings in order to aid in the detection of disease in the flock. These efforts may be critical in combating the problem. However, they have a limitation in that they cannot tell the disease type directly, and performance can be influenced by the chicken's natural structure. Moreover, in the previous works, models were trained using entire acquired images without utilizing object detection. This approach may result in reduced classification accuracy, as the presence of non-target objects in the images may negatively impact the training process. The current work uses an object detection algorithm prior to classification. Moreover, the developed models were deployed into a custom designed mobile app interface for ease of use of practical applications.

The objective of this work is to design and develop poultry disease detection and classification system that has a capability to detect and classify poultry disease from chicken dropping. The system was

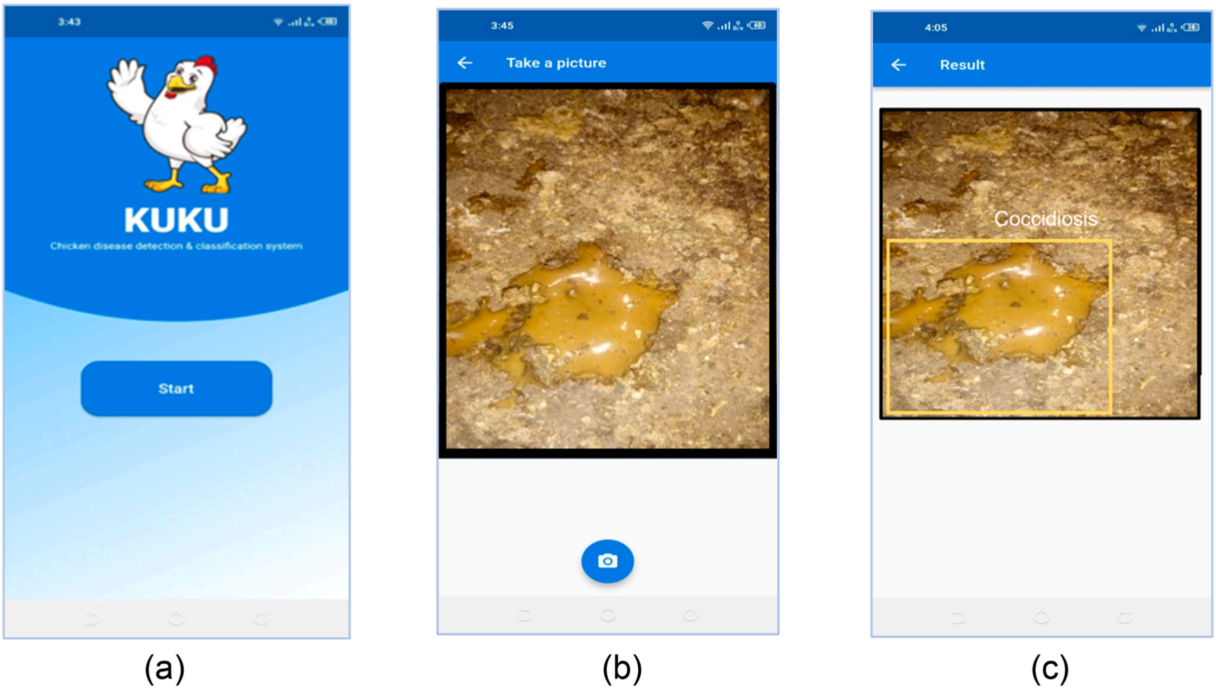

Fig. 12. Chicken disease detection and classification mobile app user interface. (a) Start screen (b) Picture acquiring screen (c) Classification result.

developed using YOLO-V3 object detection algorithm and a pre-trained ResNet50 image classification model. The object detection algorithm was applied to segment out chicken's dropping from the rest of an image scene. The segmented image is then feed into the classifier model for final classification.

In summary, the proposed system is developed to overcome the problem of human errors during external examination and complexities required for laboratory examination of chickens. Our system has a capability to identify most common poultry diseases Coccidiosis, Salmonella, and New Castle Disease from chicken's faecal image. The developed system can be used in poultry farms to assist farmers and veterinarians. It can be also used as baseline for other researchers for further improvement of the system. More dataset collection, especially for diseases that are not included in this study can improve the accuracy and quality of the system.

5. Conclusion

This study presented poultry disease detection and classification system from chicken faecal images. The system uses two core algorithms: YOLO-V3 object detection algorithm, for region of interest segmentation, and pre-trained ResNet50 model for detection and classification of poultry diseases from the segmented image. Various hyperparameter optimization techniques have been performed during system development and best performing models were selected and deployed on a mobile application, which was developed during the study using flutter mobile application development framework.

Our experimental results show that, the developed chicken disease detection and classification system has a capability to identify three common poultry diseases in high accuracy and can be used in farms to assists poultry farmers and veterinarians.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Funding

Not applicable.

CRediT authorship contribution statement

Mizanu Zelalem Degu: Conceptualization, Funding acquisition, Methodology, Supervision, Visualization, Project administration. **Gizeaddis Lamesgin Simegn:** Conceptualization, Funding acquisition, Methodology, Supervision, Visualization, Project administration.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

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